



Don't Get Kicked

Predict whether Car Purchase
at Auction is a 'Lemon'

BIOS 635: Final Project Report
Junead Khan

What is a 'Lemon Car'



Aim:

Can we predict
whether a car bought
at an auction is a
Lemon Car?

The Dataset

Training Dataset:

72,893
records

Test Dataset:

47,707
records

32 Unique Features

PurchDate, Auction, VehYear, VehicleAge, Make, Model, Trim, SubModel, Color, Transmission, WheelTypeID, WheelType, VehOdo, Nationality, Size, TopThreeAmericanName, MMRAcquisitionAveragePrice, MMRAcquisitionCleanPrice, MMRAcquisitionRetailAveragePrice, MMRAcquisitionRetailCleanPrice, MMRCurrentAuctionAveragePrice, MMRCurrentAuctionCleanPrice, MMRCurrentRetailAveragePrice, MMRCurrentRetailCleanPrice, PRIMEUNIT, AcquisitionType, AUCGUART, KickDate, BYRNO, VNZIP, VNST, VehBCost, IsOnlineSale, WarrantyCost

Holding Out Data

Training Dataset:

72,893
records

Split Training Dataset:

$2/3$

Hold Out Dataset:

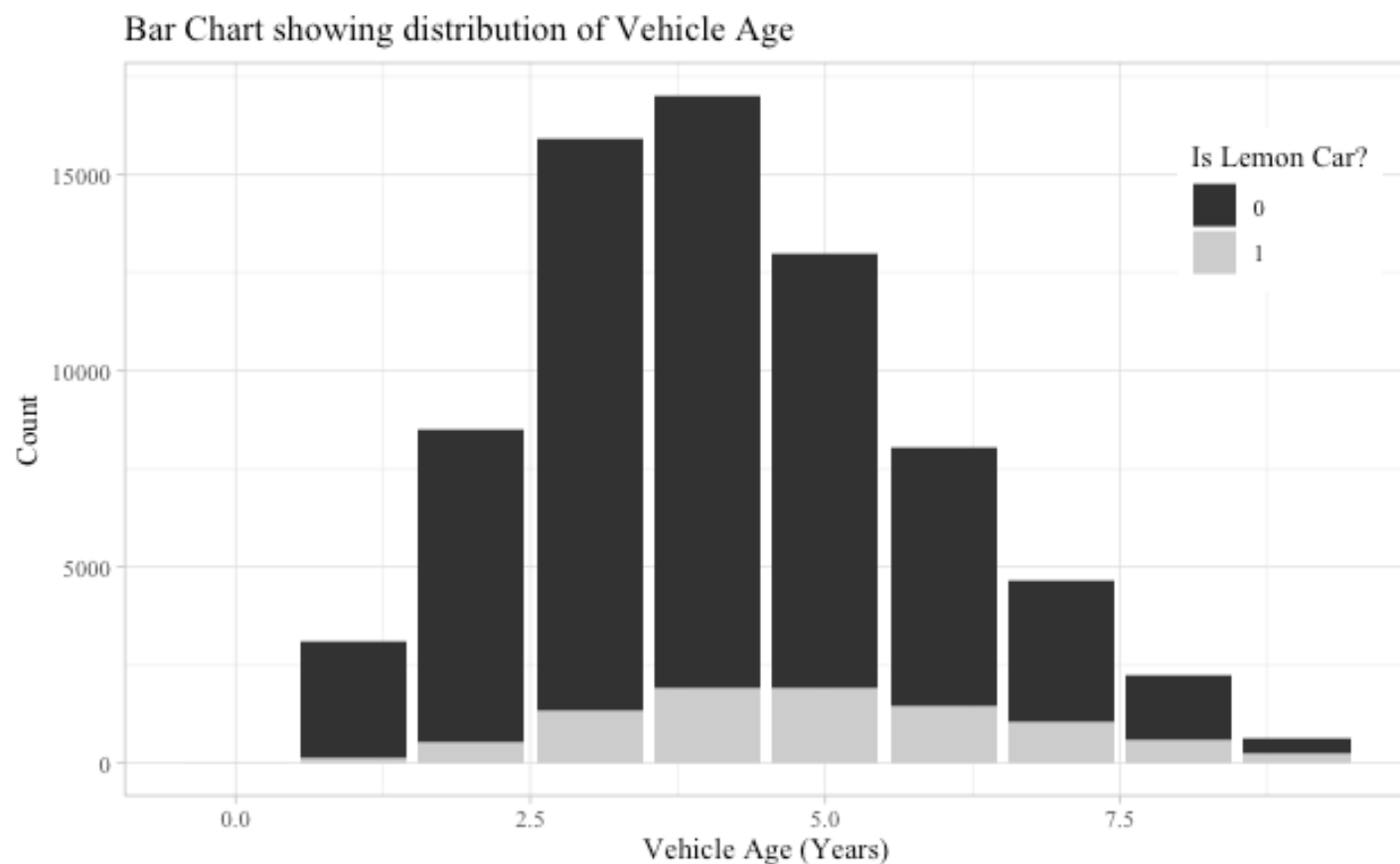
$1/3$

1. Data Cleaning

- Variables with high number of NULL removed (>90%)
- Variables deemed to be not relevant were removed
- Transmission Variable NULL WheelType = 'Steel' Wheels
- One-to-one mapping between WheelType and WheelTypeID
- Changed String 'NULL's to NA in R
- Converted MMR variables to numeric
- Converted other character variables to Factors.

2. Data Exploration

2.1 Vehicle Age



Mean Age: 4.18

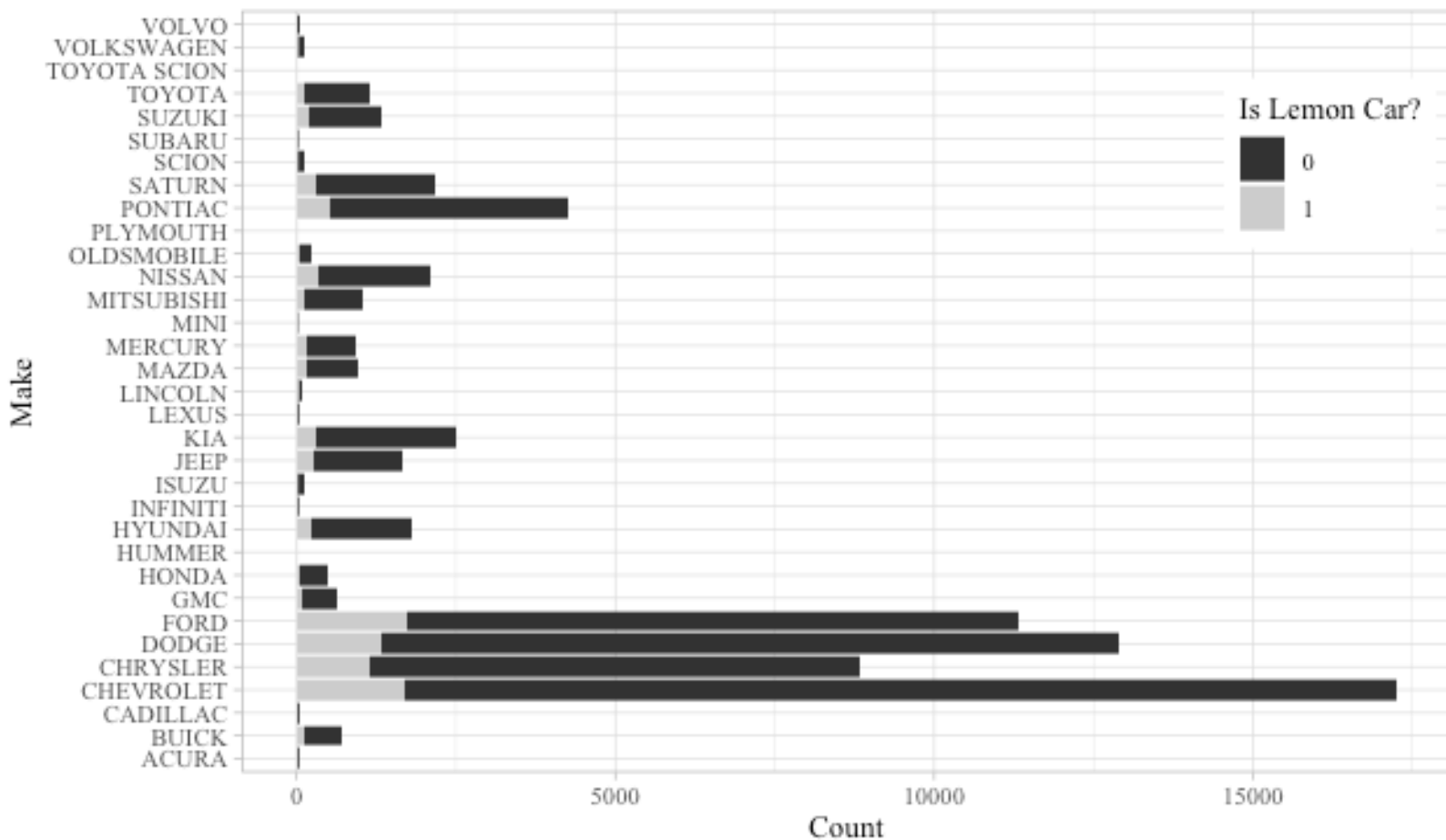
Median Age: 4.00

Newest Car: 0 Years

Oldest Car: 9 Years

2.2 Vehicle Make

Bar chart showing distribution of car makes in the dataset.

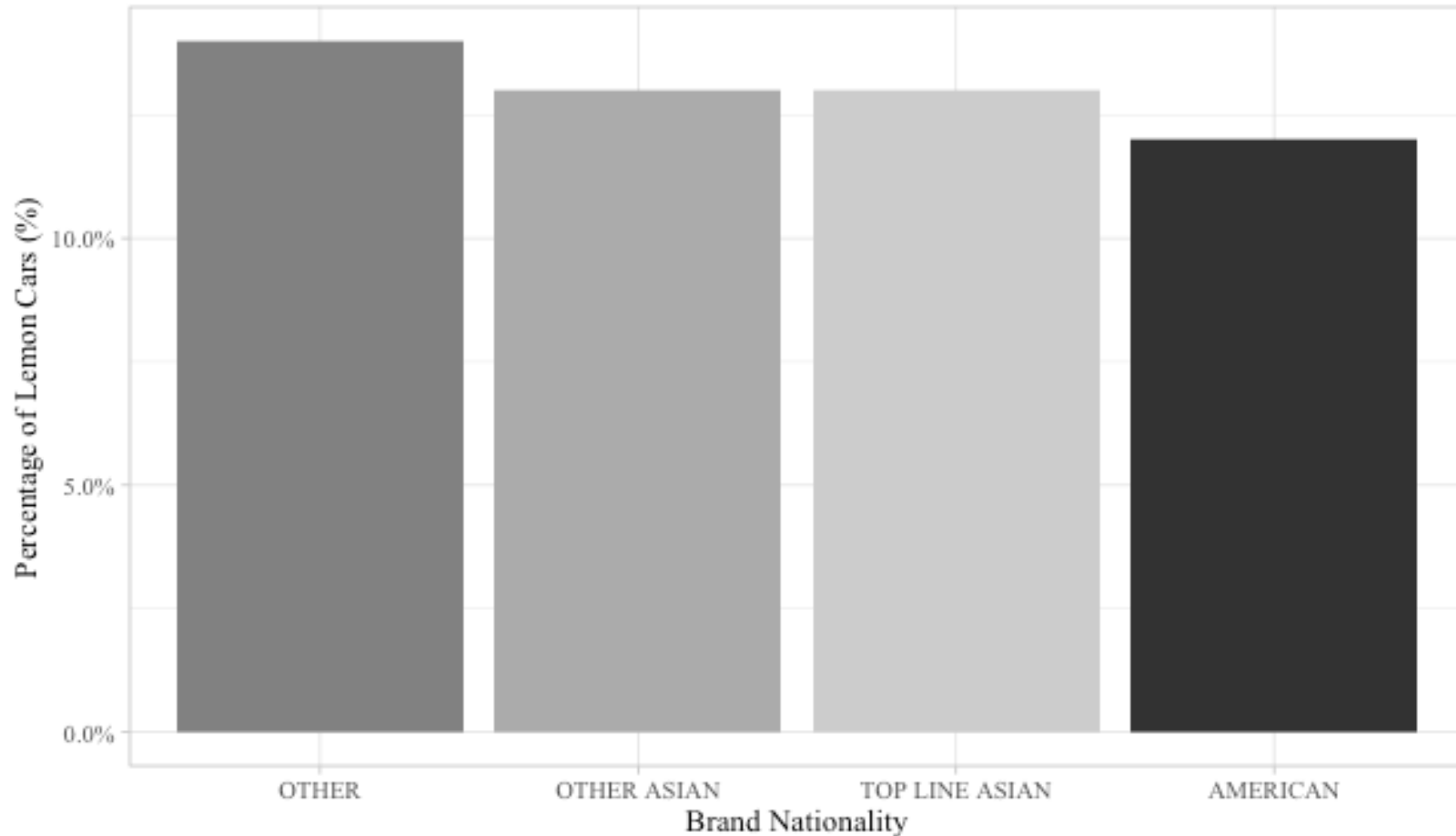


American Manufacturers overrepresented
e.g. Chevrolet, Ford, Chrysler, Dodge, Cadillac

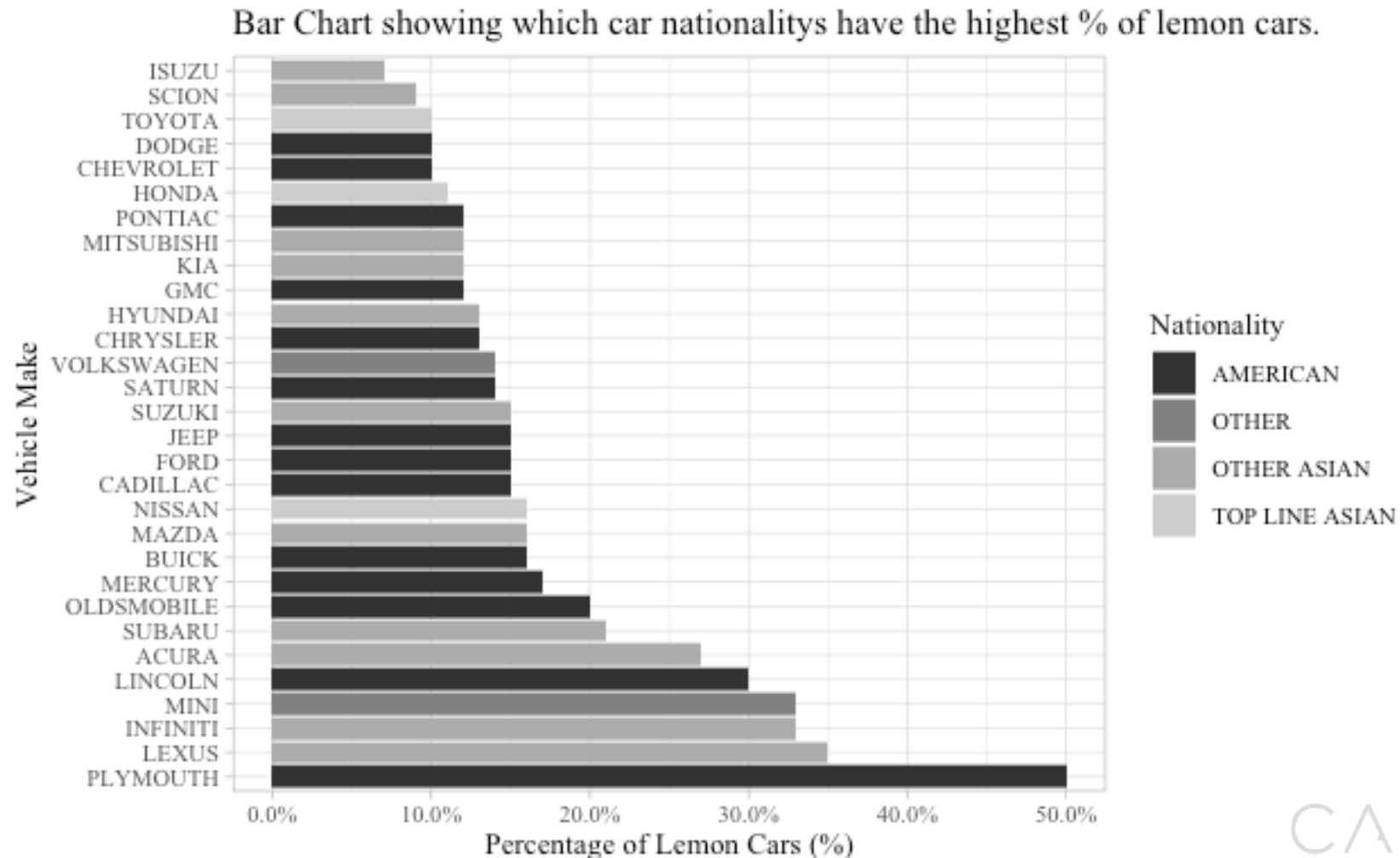
Asian Manufacturers underrepresented
e.g. Toyota, Honda, Nissan, Subaru

2.3 Vehicle Nationality

Bar Chart showing which nationalities have the highest % of lemon cars.

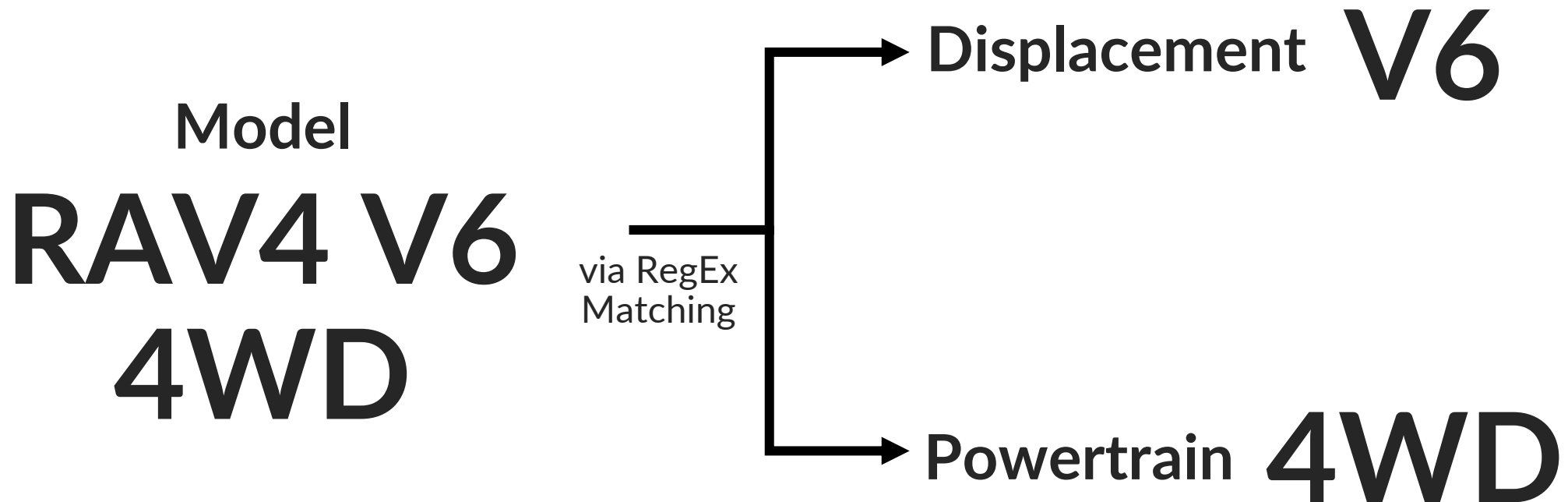


2.4 Vehicle Make Relative to Proportion



3. Feature Engineering

Using Model to create 2 new features



Price Difference

MMRAcquisitionAveragePrice

\$12,000

Model

\$7,000

Difference

price_difference

\$5000

Miles Travelled Per Year

VehOdo	Vehicle Age		miles_per_year
34,000	5	Ratio →	6,800
36,000	2	Ratio →	18,000

4. Feature Selection

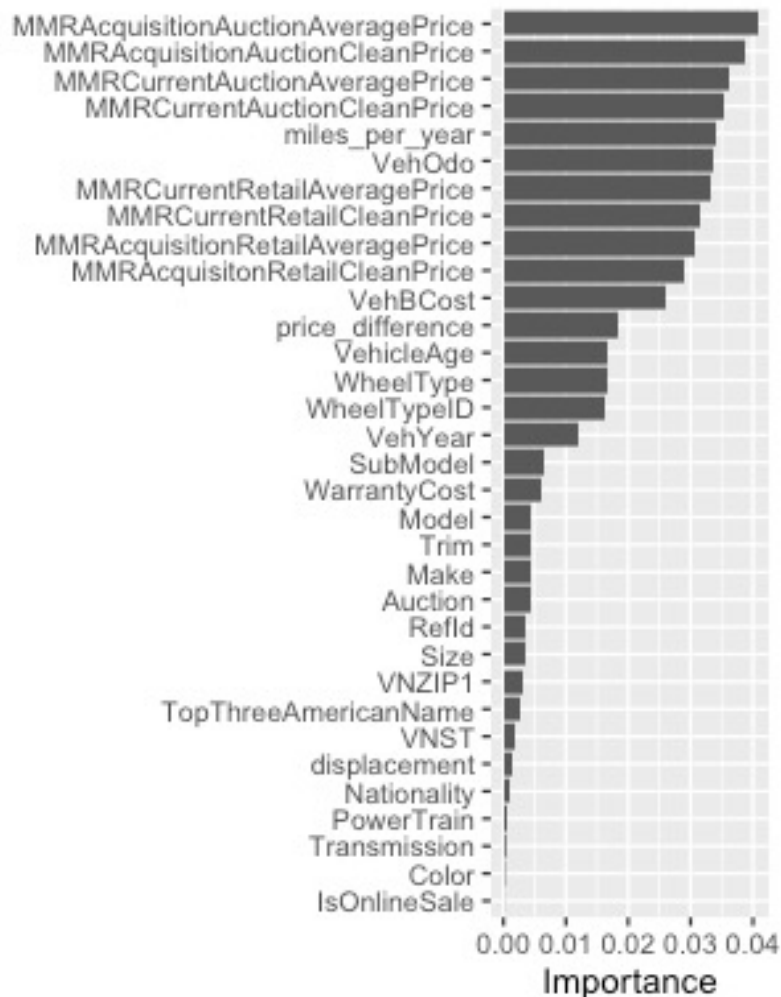
Random Forest

500 Trees

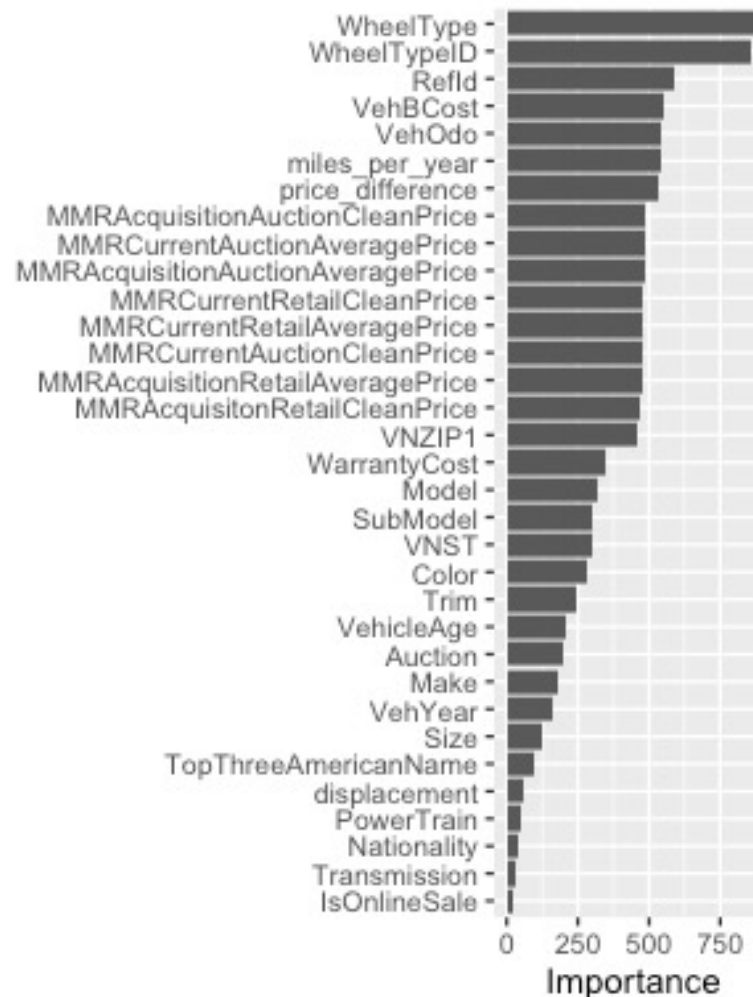
Variable Importance

Variable Importance

Permutation Importance



Gini Impurity



5. Modelling & Evaluation

Accuracy

Sensitivity

AUC

5.2 Baseline Performance

Accuracy

0.8870

5.3 Logistic Regression

Features Included:

MMR features,
miles_per_year, VehOdo,
VehBCost, VehOdo,
WheelType,
WheelTypeID, and
VNZIP1

Model Performance Metrics for Logistic Regression Model

Accuracy	Sensitivity	AUC
.8968	.2458	.7398

5.4 Random Forest

Package ‘ranger’

July 14, 2021

Type Package

Title A Fast Implementation of Random Forests

Version 0.13.1

Date 2021-07-14

Author Marvin N. Wright [aut, cre], Stefan Wager [ctb], Philipp Probst [ctb]

Maintainer Marvin N. Wright <cran@wrig.de>

Description A fast implementation of Random Forests, particularly suited for high dimensional data. Ensembles of classification, regression, survival and probability prediction trees are supported. Data from genome-wide association studies can be analyzed efficiently. In addition to data frames, datasets of class 'gwaa.data' (R package 'GenABEL') and 'dgCMatrix' (R package 'Matrix') can be directly analyzed.

Model Performance Metrics for Random Forest Model

Accuracy	Sensitivity	AUC
.9000	.2425	.7242

5.4 Gradient Boosting

500 Trees

Shrinkage: 0.01

Interaction Depth: 5

5-Fold Cross Validation to
Reduce Overfitting and
aid in Parameter Tuning

Model Performance Metrics for Gradient Boosting Model

Accuracy	Sensitivity	AUC
.9012	.2475	.7417

Comparison of Results

Model Performance Metrics for All Models. *Darker shade represents better performance.*

Model	Accuracy	Sensitivity	AUC
Logistic Regression	.8968	.2458	.7398
Random Forest	.9000	.2425	.7242
Gradient Boosting	.9012	.2475	.7417

6. Kaggle Submission Result

My Public Score:

0.1375

Top 500 Entries

Best Submission on Kaggle:

0.2672

1st Place Entry

7. Areas of Improvement

- Top Kaggle Submissions used Ensemble Methods
- One-Hot Encoding
- Dataset was heavily class-imbalanced
 - Under sampling or Class Weighting



Thank you for listening

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